Reducing False Alarms in Vision Based Fire Detection with NB Classifier in EADF Framework

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Abstract- Computational vision-based fire and flame detection has drawn significant attention in the past decade with camera surveillance systems becoming ubiquitous. Signal and image processing methods are developed for the detection of fire, flames and smoke in open and large spaces with a range of up to 30m to the camera in visible-range (IR) video. This paper proposes a new approach to computational vision-based fire and flame detection by using a compound algorithm and a decision fusion framework with Naïve Bayes classifier as classification tool. The compound algorithm consists of several sub-algorithms, the fusion network is to fuse the results obtained by each of these sub-algorithms and Naïve Bayes classifier is useful for the final classification. This approach is to improve the accuracy of fire and flame detection in videos and to reduce the false alarm rate to a great extent.

Index Terms- Computer vision, decision fusion, feature extraction, fire detection, generic color model, image processing, online learning.

I. Introduction

Surveillance cameras have become an important aspect in security and have become a necessity to keep proper check. As the number of surveillance cameras being installed in various fields increased, computational vision based object detection has become vital worldwide. In computer vision, this is the task of finding a given object in an image or video sequence. Several image processing techniques are developed for the detection of different objects from images and video sequences. Detection of fire, flame and smoke is a subfield of vision based object detection and is potentially a useful technique in the implementation of both indoor and outdoor fire alerts. It offers advantages over the traditional methods.

Since fire is a complex but unusual visual phenomenon, unlike normal objects, it has dynamic texture. Due to its frequent shape and size alterations, computational vision-based fire and flame detection algorithms are upon multi-feature-based approaches. The hope and the goal of such algorithms is to find a combination of features whose mutual occurrence leaves fire as their only combined possible cause [1]. Colour, motion, shape, growth, flickering, and smoke behaviour etc. are some of the low level distinctive features of fire regions. Along with these distinctive features, spectral, spatial and temporal features are also used for distinguishing fire regions artificially.

II. Related Works

W. Phillips, M. Shah, and N. Lobo. [2] propose a system that uses motion and color information computed from video sequences to locate fire. First of all a Gaussian-smoothed color histogram is created and then uses an approach based on this histogram for the detection of fire-colored pixels. Then, temporal variation of pixels is calculated and by using these calculations the algorithm determines which of these pixels actually fire pixels are. Next, using an erode operation, some spurious fire pixels are automatically removed and using region growing method, some missing fire pixels are found. The technique detects fire reliably under normal conditions. Lack of hardware implementation is a disadvantage. So the algorithm can only be used as part of a robust, real-time system. High false alarm rate is another disadvantage.

A technique based on Markov models was presented by Toreyin, B.U. et. al. in [3] to detect flames in video. In this technique, Markov models are generated to represent the flame and flame colored ordinary moving objects. Then these models are used to distinguish flame motion from motion of flame colored moving objects. Spatial color variations in flame are also evaluated by the same Markov models, as well. Final decision is made by combining these clues. Advantages of hidden Markov models based flame detection are its' robustness and computational efficiency to detect flames in color video. False alarms due to ordinary motion of flame colored moving objects are greatly reduced. It has the following disadvantage. Since the spreading characteristics of flame depend on the strength of the wind, it is impossible to use the same location within a fixed time to model the periodic behavior of flame boundaries.

Luis Merino et. al. [4] presents a framework for cooperative fire detection by means of a fleet of heterogeneous UAVs. Cameras and other types of fire sensors are incorporated into UAVs. Cameras capture visual images and sensors sense infrared. Computer vision techniques are used to detect and localize fires from these information. The algorithm is based on the fact that visual color images of fire have high absolute values in the red component of the RGB coordinates and that the ratio between the red component and the blue and green components. The algorithm uses UV radiation characteristic of fire also. It uses a cooperative state estimation procedure, which estimates the position of the fire and the nature of the fire. Data association is a key problem. Here a simple nearest neighbor strategy is considered. However, in complex scenario, this can lead to bad association. For this kind of sensor, a grid-based localization technique is more suitable for fire localization.

An algorithm which is based on the temporal variation of fire intensity captured by a visual image sensor was proposed by G. Marbach, M. Loepfe, and T. Brupbacher in [5]. Analysis of the full image sequences helps to select a candidate flame region. Characteristic features extraction is done from the candidate flame region and combined to determine the presence of fire or non-fire patterns. If the fire pattern persists over a period of time, fire alarm is triggered. The ''YUV'' representation of the video data is assumed here. Luminance and chrominance are computed. The time derivative of the luminance is zero for the stationary scene regions, and is non-zero for moving objects. Six characteristic features are extracted: Luminance, frequency, amplitude, number of active pixels, number of saturated pixels, number of fire-color pixels. Finally, an "indicator" is used to describe the presence of fire or non-fire.

It has high reliability and a strong robustness towards false alarm in normal environments. The reaction time and the sensitivity of the algorithm can be adjusted according to the scene complexity and light condition, increasing the flexibility. It has the following disadvantages also. False alarm rate is very high under specific lighting conditions. High brightness or luminance causes image pixels to saturate.

Turgay Celik and Hasan Demirel [6] proposed a rule-based generic color model for flame pixel classification. The proposed algorithm uses YCbCr color space. YCbCr color space is more effective to separate the luminance from the chrominance than color spaces such as RGB or rgb. The key idea is that the fire pixels shows the characteristics that their Y color value is greater than Cb color value and Cr color value is greater than the Cb color value. Even though RGB color space can be used for pixel classification, it has disadvantages of illumination dependence. It means that if the illumination of image changes, the fire pixel classification rules cannot perform well. So it is needed to transform RGB color space to one of the color spaces where the separation between intensity and chrominance is more discriminate. Since the flame region is generally the brightest region in the observed scene, the mean values of the Y, Cb and Cr channels, in the overall image contain valuable information.

The number of arithmetic operations for the proposed color model is linear with image size and algorithm is of low computational complexity. This makes it eligible for the real-time applications. It has the following disadvantage. Non-fire regions such as car lights, flame reflections, and changing neon lights often exhibit a similar pattern over time; hence, this method cannot provide time analysis of the spread of fire regions in a video sequence.

C. Ho [7] proposed a novel real-time machine video-based flame and smoke detection method. This method can easily be incorporated with a surveillance system for early alerts. In this technique, potential flame and smoke candidate regions are identified by checking weightage of the statistical distribution of the spectral, spatial and temporal probability density is with a fuzzy reasoning system to identify. Smoke and flame color histogram models are compared in HSI color space and the spectral probability density is represented. The spatial probability density is represented by computing the flame and smoke turbulent phenomena with the relation of perimeter and area. Flickering area from the video sequences are extracted and alias objects from the flame and smoke region are separated to represent the temporal probability density. Experimental results under a variety of conditions show that the proposed method is capable of detecting flame and smoke reliably. This system requires additional research on fuzzy reasoning in complex moving environments and it requires a complementary tracking algorithm for multiple concurrent fire regions.

A new vision sensor-based fire-detection method was proposed by Byoung ChulKo et. al. in [8] for an early-warning fire-monitoring system. First, any candidate region detection method such as the detection of moving regions and fire-colored pixels is used for the detection of candidate fire regions. Next, a luminance map is made. The key idea behind the generation of this map is that the fire regions generally have a higher luminance contrast than neighboring regions. This luminance map is used to remove non-fire pixels. Thereafter, the algorithm creates a temporal fire model with wavelet coefficients. This temporal fire model is applied to a two-class support vector machines (SVM) classifier. The kernel used by the classifier is a radial basis function (RBF) kernel. The SVM two-class support vector machine with RBF kernel is then used for the final fire-pixel verification. This approach has strong robustness to noise such as smoke, and exquisite differences between consecutive frames. This approach has got some disadvantages. Occurrence of frequent false alarms because it uses heuristic features. SVM classifier needs additional computation time depending on feature dimension.

Paulo Vinicius Koerich Borges, and Ebroul Izquierdo [9] proposed a method that analyses the changes of specific low-level features in the consecutive frames. This analysis helps describing potential fire regions. These low level features are area size, color, boundary roughness, surface coarseness, and skewness within estimated fire regions. The gradual modification of each one of these features is evaluated, and then combines the results according to the Bayes classifier for accurate recognition of fire. In addition, the classification results are significantly improved by using a priori knowledge of fire events captured in videos. It has the following advantage. Very fast processing, making the system applicable for real time fire detection as well as video retrieval in news contents. High brightness or luminance causes image pixels to saturate.

Yusuf Hakan Habiboglu et. al. [10] proposed video fire detection system which uses a spatio-temporal covariance matrix of video data. This system divides the video into spatio-temporal blocks and computes covariance features extracted from these blocks to detect fire. Feature vectors are classified using an SVM classifier. The SVM classifier is trained and tested using various video data containing flame and flame colored objects. The feature vectors takes advantage of both the spatial and the temporal characteristics of flame colored regions. This method is a computationally efficient method. But if the fire is small and far away from the camera or covered by dense smoke the method might perform poorly. Since the method assumes a stationary camera for background subtraction it cannot correctly classify most of the actual fire regions.

David R. Thompson, William Johnson, and Robert Kremens [11] proposed a method for the detection of wildfire which is used in airborne or orbital image sequences. This technique captures multiple overlapping frames using space vehicles and recognizes stable interest point features in these overlapping frames. It analyses motion between contiguous frames and detects candidate regions over time. To improve sensitivity, the final detection decision joins signal strengths from multiple view. The algorithm is computationally tractable for real-time use on autonomous robotic platforms and spacecraft. It has got higher acquisition rates and potentially improved coverage for remote monitoring. Multiple detections problem is a disadvantage.

Byoung Chul Ko, Sun Jae Ham, and Jae Yeal Nam [12] proposed a novel method using fuzzy finite automata (FFA) for fire-flame detection. FFA is used with probability density functions based on visual features. It provides a systemic approach to handling irregularity in computational systems and it has the ability to handle continuous spaces by combining the capabilities of automata with fuzzy logic. First, using background subtraction moving regions are detected, and then identify the candidate flame regions by applying flame color models. As the flame regions have a continuous irregular pattern, the variation in intensity, motion orientation and wavelet energy are used to generate probability density functions and it is then applied to the FFA.

This technique is robust for similar cases such as shadows, reflective surrounding areas, rapid changes in color and motion, and changing neon signs and it performs better if the fire is near to the camera. But if the fire is small and far away from the camera or covered by dense smoke the method might perform poorly.

J. Zhao, Z. Zhang, S. Han, C. Qu, Z. Yuan, and D. Zhang [13] proposed an approach based on SVM. A Gaussian mixture model is built based on 3D point cloud of the collected sample fire pixels and it helps to segment some possible flame regions in an image. Then the newly identified flame pattern is defined for forest, and three types of fire colors are labelled accordingly. With 11 static features and 27 dynamic features, the SVM classifier is trained and filters the segmented results. This trained SVM is used for final decision. It has the following advantage. A total of 27 dynamic features are considered for SVM based final classification, and the features are extracted from every 20 consecutive video frames. Therefore, except for accuracy, the detection algorithm can perform and give alarms in real time. It has the following disadvantages also. This approach has lower accuracy for fire with small regions, and the performance is even worse for small fires covered by smoke.

Y. Habiboglu, O. Gunay, and A. Cetin [14] proposed a video-based fire detection system which uses color, spatial and temporal information. The video sequence is divided into spatio-temporal blocks by the algorithm extracts covariance-based features from these blocks. By using these extracted features fire is detected. Feature vectors take advantage of both the spatial and the temporal characteristics of flame-colored regions. A support vector machine (SVM) classifier is used to train and test the extracted features. Since the system does not use a background subtraction method to distinguish moving regions from non-moving objects, this system can be used with non-stationary cameras to some extent. Its computational cost is low in terms of memory and processing power. The disadvantage is that if the fire is small and far away from the camera or covered by dense smoke, the method might not perform well.

Martin Mueller, Peter Karasev, Ivan Kolesov and Allen Tannenbaum [15] proposed a set of motion features based on motion estimators for computational vision-based flame detection. In general, fire motion is fast and turbulent. On the other hand, objects other than fire are having structured and rigid motion. The key idea of this algorithm consists of exploiting the difference between these two motions. Classical optical flow methods cannot be used for representing the characteristics of fire motion. So two other optical flow methods are specifically designed for the fire detection task: Fire with dynamic texture is represented using optimal mass transport scheme and saturated flames are represented using a data-driven optical flow scheme. This algorithm extracts characteristic features related to the flow magnitudes and directions from the flow fields. Then these features are used distinguish fire and non-fire motion. The technique requires minimum spatial resolution. It is robust to changes in the frame rate and it has maximum allowable bounds on the additive noise level. It has the following disadvantage. Little false detection is observed in the presence of significant noise, partial occlusions, and rapid angle change.

Osman Gunay et. al. [16] propose an entropy-functional-based online adaptive decision fusion (EADF) framework for image analysis and computer vision applications. In this framework, there is a compound algorithm which consists of several sub-algorithms. Each sub-algorithm has a weight associated with it and the weights are updated online according to the decisions of a security guard. Decision values obtained by the sub-algorithms are linearly combined with these weights. For the purpose of final classification, a Support Vector Machine is used.

Since it uses online adaptive fusion scheme, the learning duration is decreased. The error rate of this method is low. The proposed framework for decision fusion is suitable for problems with concept drift. It has the following disadvantages. Since the approach uses SVM classifier, learning takes long time. SVM algorithm has several key parameters that need to be set correctly to achieve the best classification results for any given problem. The user may, therefore, have to experiment with a number of different parameter settings in order to achieve a satisfactory result. Computationally expensive, thus runs slow.

III. USE OF NAÏVE BAYES IN THE DECISION FUSION FRAMEWORK

A better enhancement to the EADF framework to overcome its disadvantages of using SVM classifier is to introduce a Naive Bayes classifier. In the EADF framework, there exists a compound algorithm which consists of several sub-algorithms. Each sub-algorithm yields its own decision as a real number centred around zero, representing the level of confidence of that particular sub-algorithm. Each sub-algorithm has a weight associated with it and the weights are updated online according to an active fusion method in accordance with the decisions made by a security guard. So, the weight of a sub-algorithm with poor performance decreases during the training phase and the importance of that sub-algorithm becomes low in the decision making process. Decision values obtained by the sub-algorithms are linearly combined with these weights. The proposed automatic video-based wildfire detection algorithm is based on five sub-algorithms:

1) Slow moving video object detection;
2) Smoke-coloured region detection;
3) Wavelet-transform-based region smoothness detection;

4) Shadow detection and elimination; and
5) Covariance-matrix-based classification using Naïve Bayes classifier.

In this paper, for the purpose of final classification, we use Naive Bayes classifier. Various studies in image processing show that Naive Bayes classifier outperforms all other sophisticated algorithms such as SVM and is a best tool for image classification [17]. A Naive Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong independence assumptions. If these independence assumptions actually hold, a Naive Bayes classifier will converge quicker than other classifiers. Even if the NB assumption doesn't hold, a NB classifier still performs surprisingly well in practice and it need less training data. Naive Bayes classifier is Fast to train (single scan), fast to classify, and not sensitive to irrelevant features. It can handle real, discrete and streaming data well. Naive Bayes classifiers have worked quite well in many complex real-world situations. There are sound theoretical reasons for the apparently implausible efficacy of naive Bayes classifiers

IV. CONCLUSION

Computational vision-based fire detection is the task of finding the presence of fire regions in an image or video sequence. It has drawn significant attention in the past decade with camera surveillance systems. Various schemes for computational vision-based fire and flame detection had been discussed in this paper. Most of these algorithms use spectral, spatil, temporal and other low level features of fire for distinguishing it from other objects in video sequences.

EADF framework is useful to fuse a set of decisions made by several sub-algorithms and hence makes a combined decision. Naive Bayes classifier outperforms all other sophisticated algorithms and hence it can be used for the final classification in EADF frameworks. With this, detection of fire regions in video sequences can be made easier and false alarm rates can be reduced to a great extent.

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